Estimating Co-Pollutant Benefits from Climate Change Policies in the Electricity Sector: An Empirical Approach

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Selected Paper prepared for presentation at the 2017 Agricultural & Applied Economics Association Annual Meeting, Chicago, Illinois, July 30-August 1

Abstract

We develop an empirical approach for estimating co-pollutant reductions and associated health benefits resulting from climate change mitigation policies whose primary goal is to reduce CO_2 emissions in the energy generation sector. Unlike previous studies in the field of co-benefit estimation, we do not rely on engineering-based linear programming models to assess the effects of a climate change policy with regards to co-pollutant reductions. Instead, we use historical data from US power plants to empirically estimate the effects of compliance with such a policy. Our results indicate that a 1% decrease in electricity output from coal power plants in the U.S. reduces SO_2 emissions by 0.5% and NO_x emissions by 0.8%. In natural gas plants, a 1% reduction in electricity output reduces NO_x by 0.7%. Decreasing heat rate by 1% in coal plants reduces NO_x emissions by 1.2%. We use our marginal estimates to calculate total reductions of co-pollutants from the Clean Power Plan, allowing us to compare our estimates to the EPA's predictions. We find total NO_x reductions of 285,000 tons and SO_2 reductions of 263,000 tons. Neither figure is statistically different from EPA's estimates, a fact that validates our empirical approach. We provide estimates of the resulting health effects using an integrated assessment model, which suggest that the EPA could be potentially underestimating the health benefits from NO_x reductions. Overall, our results suggest that there is value in using an empirical approach to project the environmental impacts of EPA interventions, rather than relying exclusively on engineering-based analyses.

1. Introduction

In recent years, climate change policies have been receiving increasing attention (Ostrom 2009). The Paris Agreement, entered into force in November 4th 2016, sets ambitious goals for the control of greenhouse gas (GHG) emissions and has been ratified by 146 countries, including the United States. Important landmark climate change regulations include the European Union Emissions Trading System (established in 2005) as well as China's recently enacted economy-wide cap and trade system. In the US, a group of prominent conservatives recently put forward a proposal for a carbon tax that would distribute dividends directly to consumers.

While climate policies, like these, all aim to reduce GHGs (e.g., CO_2), they also provide substantial co-benefits. Regulations that reduce CO_2 emissions in the energy generation sector also reduce emissions of co-pollutants like sulfur dioxide (SO_2) and nitrous oxide (NO_X), among others. These local pollutants have significant effects on mortality and morbidity.

In this paper we demonstrate a simple empirical approach for estimating the co-pollutant emissions reductions from a carbon policy in the electricity sector. Unlike the standard approach in the literature, which relies on complex linear programming models to calculate the reductions in co-pollutant emissions, we use historical data from US power plants to estimate the co-pollutant emissions reductions that would result from a policy to reduce CO_2 emissions in the electricity sector. In addition, we examine the health impacts of our estimated reductions in co-pollutants.

We use the Clean Power Plan (CPP) to motivate, develop and validate our empirical approach. The Clean Power Plan sets CO_2 emissions reductions targets for each state's power plant sector, while allowing each state to develop its own plan for achieving the reductions. Overall, EPA projects that the CPP will reduce

CO_2 emissions from power plants in 2030 by 32% from 2005 levels, and by 19% relative to baseline levels in 2030.

We focus on the CPP for two reasons. First, power plants have two main mechanisms for reducing CO_2 emissions: (1) Reduce electricity produced in coal-fired power plants, either by reducing demand for electricity or by shifting output to less carbon-intensive energy sources, natural gas and renewables; (2) increase the efficiency of the generation process in coal-burning plants (i.e. reduce the plant's heat rate). The limited number of options for CO_2 mitigation is what makes our data-driven approach for estimating co-pollutant reductions feasible. So long as a carbon policy (like the CPP or a carbon tax) does not provide direct incentives for the reduction of co-pollutant emissions, we can use the historical variation in electricity output and heat rate to estimate the marginal reductions in SO_2 and NO_X emissions that would occur as power plants adjust their output and efficiency levels in response to a carbon regulation like the CPP. Second, focusing on the CPP allows us to assess our approach by comparing our estimates of co-pollutant emissions reductions with those provided by the EPA.

Although President Trump has ordered the EPA to review or rescind the rule, we believe that using the CPP as a framework for illustrating our approach is still useful. In this context, one can think of our estimates as providing a measure of one part of the cost of rescinding this policy, which could be substantial. The EPA estimates that the health benefits from reducing co-pollutant emissions via the CPP would be roughly as large, and perhaps more than twice as large as the climate change benefits of reducing CO_2 emissions (EPA 2015a). That is the main reason we focus on these co-pollutants - because of their important health effects. Moreover, while the effect of a carbon policy on the total amount of CO_2 emitted is relatively predictable (we would expect CO_2 emissions to approach the levels mandated by the CPP), the effect on co-pollutants is much less clear. In addition, we found little empirical evidence for how co-pollutant emissions respond to changes in CO_2 emissions.

Our analysis proceeds in two steps. Using historical data from power plants, we regress co-pollutant emissions on the two primary mechanisms for reducing CO_2 emissions – electricity output and heat rate (efficiency of production) -- in coal- and natural gas-fired power plants. Second, assuming that power plants improve efficiency and reduce output as predicted by the EPA's CPP documentation, we examine how much this would reduce emissions, using our estimated elasticities for output and efficiency.

To conduct our empirical analysis, we construct a panel dataset of US power plants, using information from the Emissions and Generation Resource Integrated Database (eGRID) (EPA 2015c). eGRID is a database of US electricity producers, reporting annual output and emissions of various pollutants (CO_2, NO_x, SO_2, etc.). Using these data, we first assess the validity of our model by estimating the impact of the two mechanisms - changes in electricity output and heat rate improvements - on CO_2 emissions. We find that a 1% decrease in electricity output decreases CO_2 emissions by 1%, while decreasing heat rate (i.e. improving efficiency) by 1% in coal plants reduces CO_2 emissions by 0.9%.[1] We then use the EPA's projections of how much coal and gas plants will reduce electricity output, and how much coal plants will reduce heat rate, along with our estimates of the effects of these mechanisms to estimate how much CO_2

[1] Reducing heatrate is not an important mechanism for reducing CO_2 emissions in natural gas plants.

emissions will fall. The reductions in CO_2 emissions that we estimate are within 1.6% of the EPA projections of a 413 million ton reduction of CO_2 in 2030.

Having demonstrated the validity of our approach, we examine the impact of the two mechanisms (electricity output and heat rate reduction) on two criteria co-pollutants, SO_2 and NO_x. We find that a 1% decrease in electricity output in coal plants decreases NO_x emissions by 0.8% and SO_2 emissions by 0.5%, while the same output reduction in gas plants reduces NO_x emissions by 0.7%. Decreasing heat rate by 1% in coal plants reduces NO_x emissions by 1.2% (in our preferred specification, heat rate does not have a statistically significant effect on SO_2 emissions). Again, we use the EPA's projected reductions in output and heat rate to compare our estimates with the EPA's estimated changes in SO_2 and NO_x emissions resulting from the CPP. Our results are in line with EPA's projections regarding SO_2 and NO_x reductions. Using our preferred specification, we estimate a 263,000 ton (20.1%) reduction for SO_2 emissions relative to the 2030 baseline, while the EPA estimates a 280,000 ton (21.3%) reduction. For NO_x, our preferred estimates suggest a 285,000 ton (22%) reduction relative to the 2030 baseline, while EPA predicts a 278,000 ton (21.5%) reduction. The EPA also provides estimates of the monetary benefit from these avoid emissions. This monetary benefit is primarily derived from avoided mortality and morbidity due to pollution. To further compare our results to the EPA's we use an integrated assessment model. We find that while the EPA is accurately capturing the health benefits from avoided SO_2, it is likely understating the value of NO_x emission reductions. Furthermore, the EPA's estimates do not account for the substantial uncertainties in this modeling framework, which we find to be important.

Although we obtain very similar results to those provided by EPA in terms of overall co-pollutant reductions, our data-driven approach offers several important benefits. First, our approach provides a much cheaper, simpler and more transparent way of estimating co-pollutant reductions, compared to the complexity of linear programming models, like the Integrated Planning Model (IPM) which is the software used by the EPA to model the impacts of the CPP. Each simulation of the IPM requires an extensive set of input parameters as well as the use of a commercial grade solver (EPA 2010). The models we run are only estimating co-pollutant elasticities. As a result, they are simple and easy to replicate, with publicly-available data. In addition, while the linear programming models generate point estimates for the projected reductions in emissions, our approach allows us to calculate standard errors and produce confidence intervals for our estimates. In doing so, we are able to incorporate some of the uncertainty around the co-pollutant reductions. Moreover, our approach is very flexible, allowing us to easily consider a variety of robustness checks. For example, we estimate co-pollutant elasticities using data only from those power plants that have above average carbon intensity (i.e. tons of CO_2 emitted per kWh of electricity produced), and we estimate elasticities for both the full sample, and using only data from the later years in our sample. Similarly, we consider a series of different scenarios for how the CO_2 reductions will be distributed to estimate the resulting co-pollutant health benefits.

The rest of the paper proceeds as follows. Section 2 provides some background on linear programming models, the standard approach for projecting the impacts of environmental regulations such as the CPP, and discusses research using these models to assess the impact of CPP and other electricity-sector regulations. Section 3 presents the eGRID data used in the paper, while Section 4 describes the empirical strategy we follow. In section 5 we present our results on the co-pollutant estimates using three different model specifications. In Section 6 we estimate the monetized health benefits from reducing co-pollutant emissions. The final section offers some concluding thoughts about our approach and the implications of our findings.

2. Related Research

Linear programming (LP) models have been widely used to forecast the effects of environmental policies on pollutant emissions and subsequent health effects (EPA 2015a; EPA 2011; EPA 2015b; EIA 2015; Burtraw et al. 1998; Chestnut and Mills 2005; Smith et al. 2012; Beasley et al. 2013). A non-exhaustive list of such models includes the National Energy Modeling System (NEMS), maintained by the Energy Information Agency (EIA), the Market Allocation (MARKAL) model developed by the International Energy Agency's (IEA) Energy Technology System Analysis Program (ETSAP), the Integrated Planning Model (IPM) developed by the EPA with support from ICF Consulting Inc. and the Haiku model developed by Resources for the Future (RFF). While there are significant differences among those models, there is a common underlying structure in the way they operate. They all model a wide range of energy related sectors (i.e. energy generation, fuel production, transportation, etc.) with varying levels of detail and aim to minimize an objective cost function subject to a series of constraints. The objective function minimizes the net present value cost of investing and operating the energy sectors. Constraints include operational limitations (e.g., capacity at which power plants operate, fuel efficiency of light-duty vehicles, etc.), demand-related constraints (e.g., consumer demand for energy use) as well as policy-related constraints such as those imposed by the CPP.

We examine the IPM in more detail, because it is the LP model the EPA used to generate its projections for the CPP. The IPM is a multi-region, dynamic, deterministic LP model of the entire US energy sector. Under the assumption of perfect foresight, the model yields a least-cost solution that meets energy demands given a series of constraints. Power plants with similar characteristics are aggregated to construct what IPM calls the "model plant". For example, the 15,023 generating units in the US are aggregated into 4,738 model plants within the IPM. For each plant, the IPM considers a series of input values such as type of fuel used, heat rate, local pollutant control devices, and capacity factors, whose values are determined based on engineering estimates. Based on that information, the model provides emission rates for a variety of pollutants including CO_2, SO_2, NO_x, HCI and mercury (EPA 2010). The model projects changes in emissions from changes made to the projected input levels. The changes in emissions are perfectly determined by changes in the inputs used in the electricity generating process. In contrast, in our approach, we econometrically estimate the relationship between emissions and the two CO_2 abatement mechanisms, output reduction and heat rate reduction using data from power plants, and then use those estimated elasticities to project emissions reductions based on the EPA's projections for how much facilities will reduce output and heat rate in response to the CPP. We do not view this approach as a substitute to existing LP models. Rather we believe that our work contributes a complementary approach to projecting the impacts of regulations that induce changes in plant behavior.

The LP models discussed above (including the IPM) have long been used in in the literature to assess the ancillary benefits of climate change policies. Bell et al. (2008) conduct a comprehensive review of that research and discuss a series of papers that take that approach (Aunan et al. 2004; Cifuentes et al. 2001;

Dessus and O'Connor 2003). In addition, examples of environmental policies affecting power plants that have been evaluated using LP models include the US Acid Rain Program (Burtraw et al. 1998; Chestnut and Mills 2005) and the Mercury and Air Toxics Standards Rule (Smith et al. 2012; Beasley et al. 2013).

Some of the most recent work on co-benefits estimation using LP models includes work by Burtraw et al. (2015), Driscoll et al. (2015), Levy et al. (2016) and Rudokas et al. (2015). Driscoll et al. (2015) use EPA's IPM to derive emissions estimates from 2,417 fossil fueled power plants in the US. Those projected emissions are then used to estimate public health co-benefits. Driscoll et al. (2015) is one of the few papers that develop alternative scenarios of CO_2 emissions reductions that closely follow the targets set by the CPP and estimate the co-benefits from reductions in ozone and particular matter. Their results suggest that carbon regulations can provide immediate health benefits whose magnitude and spatial distribution depends largely on the way the standards are designed. Burtraw et al. (2015) consider an expanded set of policy designs for carbon reductions by allowing for a tradable performance standard that affects different groups of power generators. They report results that allow trading between: 1) coal-fired power plants, 2) fossil fuel plants, and 3) all electric generators. The authors use the Haiku electricity market model to estimate emissions and compliance costs under the different policy scenarios. They find that under different rates of flexibility of the policy design (e.g., allowing for trading among a greater set of generating units) emissions rates and marginal abatement costs do not move in the same direction. However, all of the policy scenarios they examine provide positive net benefits. Rudokas et al. (2015) use the MARKAL model to estimate changes in SO_2, NO_x and CO_2 based on six climate change mitigation scenarios. The authors consider a series of policies that affect sectors other than electricity (e.g., the transportation and biofuel sectors). The majority of their scenarios include CO_2 targets that are less stringent than those of the CPP. Their low carbon tax scenario shows decreases in both SO_2 and NO_x while their more stringent high carbon tax scenario predicts NO_x increases by the electricity sector.

While our work is very closely connected to the literature projecting regulatory impacts using LP models (discussed above), we also see a linkage with the literature of retrospective studies that estimate the ex post effects of regulations and compare them with ex ante projections (for an overview of retrospective studies see Kopits et al. 2014). Work in that literature includes several case studies estimating regulatory compliance costs, which the authors then compare with ex ante projections of these costs. These case studies examine a variety of EPA regulations including the Cluster Rule and the MACT 2 Rule (Morgan, Pasurka, and Shadbegian 2014), regulations on the use of methyl bromide (Wolverton 2014), limits on arsenic in drinking water (Morgan and Simon 2014), and the 1998 Locomotion Emissions Standards (Kopits 2014).

Similarly, the Resources for the Future (RFF) Regulatory Performance Initiative focuses on estimating the effects of different EPA regulations and comparing these estimates with ex ante projections. Research under this Initiative has looked at a wide variety of regulations including the Air Toxics Program, the Endangered Species Act, and the Clean Water Act (Taylor, Spurlock, and Yang 2015; Fraas and Egorenkov 2015). Although these papers exploit ex post data, which are not available for the CPP, they are similar in spirit to ours, as they focus on assessing ex ante projections of regulatory impact. We take a similar approach, but rather than using ex post data, we use historical data to empirically derive projections of the impact of the CPP, and compare our projections with those derived using EPA's IPM model.

3. Data

We obtain data from eGRID, for the following ten years: 1998-2000, 2004-2005, 2007, 2009-2010, 2012 and 2014[2] (EPA 2015c). eGRID reports annual electricity output as well as emissions of various pollutants (CO_2, NO_x, SO_2, etc.) at the plant level for utility and non-utility steam units with a capacity of at least 25 megawatts (EPA 2008). EPA uses two separate approaches to gather the emissions data reported in eGRID. For the majority of facilities, the emissions data are not observed, but instead are imputed based on electricity output. However, for the remaining facilities, the emissions data come from direct observations that are reported to EPA's Emissions Tracking System/Continuous Emissions Monitoring (ETS/CEM). Because our approach is based on estimating the relationship between electricity output and emissions, the observations with imputed (as opposed to observed) emissions data are not useful. Therefore, we only use data from plants whose emissions are observed directly (not imputed) in our analysis.

Out of the 8,903 power plants in the e-Grid dataset, 1,511 report observed emissions to ETS/CEM in at least one year. Importantly, these plants also tend to be the largest, producing the majority of electricity. Table 1 presents the annual net generation for the two sets of plants and shows that even though we are only using 17% of the total number of power plants in our sample, we are still capturing the majority of electricity produced, particularly in more recent years.

For each of these plants, eGRID provides data on our variables of interest: emissions of CO_2, SO_2, and NO_x, electricity generation and the heat rate for coal plants. In addition, eGRID also provides boiler-level data on pollution-control devices for all plants (the list of devices is found in Appendix 1). Using the information on pollution control, we construct two variables that roughly capture the plant's use of pollution control devices, for SO_2 and for NO_x emissions. Specifically, for each plant we measure the proportion of boilers that are equipped with at least one pollution control device for SO_2 and for NO_x, respectively.

For our analysis, we restrict attention to coal and natural gas power plants. We only include coal plants that produce at least 99% of their electricity from coal, and the same for natural gas plants (at least 99% of output is from natural gas). We exclude the relatively small number of plants that use a mix of fuels, because in those cases we cannot attribute the emissions by fuel type; eGRID does not report emissions by fuel type. We also exclude the handful of plants that produce electricity using renewable energy sources (33 plant-year observations), because they emit trivial amounts of SO_2 and NO_x, and we exclude oil-burning plants because they are very small, too small to noticeably affect our results.

In order to be able to compare our empirical estimates with EPA's projections we need to use data only from those plants that will be producing electricity in 2030, since that is the last year of compliance with the CPP. Therefore, we drop all observations from plants that closed during the time period of our sample

[2] We did not use eGRID data from 1996 and 1997 because for those years, the heat rate information was not available. Data for intervening years (i.e. 2001-2003, 2006, 2008 and 2011) are not available through eGRID.

and from plants that are projected to close in future years (i.e. before 2030)[3]. As a result, we drop 748 observations from 119 coal plants, and 636 observations from 109 gas plants.

After excluding a small number of observations with missing data, we end up with a sample of 859 plants comprising 5,250 plant-year observations: 1594 observations from 212 coal plants, and 3,656 observations from 647 natural gas plants.

Table 2 provides summary statistics for the coal and natural gas plants in our sample. The average coal plant in our sample is more than five times larger than the average gas plant in terms of electricity generation, and it emits more than twelve times as much CO_2. While the difference in CO_2 emissions is large, when we compare emissions of local pollutants we observe truly enormous differences between coal and natural gas plants. Coal plants emit more than 50 times more NO_x than natural gas plants, and more than 5000 times more SO_2. These differences underlie the CPP's effort to shift from coal to natural gas.

Figure 1 shows how total net generation from coal and gas plants in our sample has changed over time. Because coal plants are so much larger than natural gas plants, coal is responsible for the majority of net generation, even though there are more natural gas plants. However, over the past several years generation from natural gas has increased markedly following the innovations in hydraulic fracturing and horizontal drilling technology as well as discoveries of new natural gas fields. At the same time, coal-fired generation grew very slowly until 2007, and has been gradually declining since (with a small upturn in 2014).

Figure 2 shows the trends in emissions over time for the plants in our sample. CO_2 emissions have remained fairly stable, increasing slightly over the time period of our sample. Emissions of SO_2 and NO_x have been declining over time, due primarily to the increasing adoption of pollution control devices (especially in coal plants).

One of the limitations of our work is that eGRID does not include data on emissions of particulate matter (PM). However, according to the EPA, directly emitted $PM_{2.5}$ produces less than 10% of the monetized health benefits derived from co-pollutants across the different emissions reductions scenarios. The majority of the health benefits result from co-pollutant reductions, which serve as precursors for the formation of $PM_{2.5}$. Therefore, we do not believe that this omission poses a serious challenge to the implications of our analysis.

4. Empirical Analysis

Our primary goal is to assess how much each of the two primary mechanisms for reducing CO_2 emissions from electricity generation– increasing the efficiency of coal-fired plants by reducing the heat rate, and reducing output from coal plants, by reducing demand and/or by shifting output to renewable energy and

[3] We obtain data on plant closures and projected closures from the EIA-860 data.

natural gas plants – affect emissions of SO_2, and NO_x. To do so, we estimate a series of panel-data regressions. We estimate separate models for coal and gas-fired plants, as the effect of each mechanism will vary with the type of plant. Our baseline models have the following structure:

$$\ln(\text{Emissions}_{pit}) = B_1*\ln(\text{Output}_{it}) + B_2*\ln(\text{Heat rate}_{it}) + B_3*\text{Pollution controls}_{it} + c_i + B_4*(\text{Year}_t*c_i) + w_{st} + e_{pit},$$
(Coal plants)

$$\ln(\text{Emissions}_{pit}) = A_1*\ln(\text{Output}_{it}) + A_2*\text{Pollution controls}_{it} + g_i + A_3*(\text{Year}_t*g_i) + v_{st} + u_{it},$$ (Natural gas plants)

where Emissions_{pit} indicates the annual emissions of pollutant p, by facility i, in year t. We only include heat rate in the coal plant regressions, because according to the EPA, gas plants cannot substantially reduce CO_2 emissions through heat rate reductions (EPA 2015a). The coefficient on output will identify two sub-mechanisms: reducing demand for electricity, and shifting output from higher-carbon coal, to lower-carbon gas and zero-carbon renewables. In the case of switching from coal to gas, the net effect will depend on the difference in the output coefficient in the coal and gas models. In contrast, in the case of switching from coal to renewables, the coefficient on output in the coal model captures the full reduction of emissions, because renewables do not emit substantial amounts of SO_2 and NO_x.

In some models we include a dummy variable indicating whether or not the facility has adopted any of the pollution controls devices listed in Appendix 1. In all models, we include plant fixed effects to control for unobserved differences in abatement technology and efficiency across facilities, state-year fixed effects to control for unobserved variation in economic conditions, regulatory stringency, and other state-level factors, and plant-specific time trends to control for plant-specific changes in technology. We cluster our standard errors at the state level to account for any correlation over time and across plants within a state. Finally, because we are interested in aggregate emissions, we weight observations by the plant's output level.

While these fixed effects eliminate a substantial amount of the potential endogeneity bias, we recognize that output, heat rate, and emissions are chosen simultaneously, and it is not possible to perfectly identify a causal relationship in our model. In particular, it seems plausible that as plants discover cleaner processes and technologies, they would increase output, reduce heat rate, and reduce emissions. As a result, the coefficients on output and heat rate would be inflated by the underlying effect of these innovations. However, we do not believe that this is a big problem empirically, because our results change very little when we omit plant fixed effects from our model. The plant fixed effects, along with the plant-specific time trends, should purge the large majority of these kinds of effects (more efficient plants produce more, at lower heat rate, and with lower emissions). Moreover, we control for some of these technologies with our control device dummy variables. We believe that any remaining time-varying sources of endogeneity should have very little impact.

5. Results

We estimate elasticities of emissions with respect to output and heat rate in three different specifications. Using the emissions elasticities, we calculate the overall projected emissions reductions relative to EPA's 2030 baseline projections in order to compare our estimated emissions reductions with those of the EPA.

For each pollutant (CO_2, SO_2 and NO_x) we run: 1) a baseline model that includes our full sample (i.e., the ten years for which we have data between 1998-2014); 2) a model that includes newer data only (2007-2014); and 3) a model that includes plants with carbon intensity above the median level in 2014. We will refer to these specifications as "baseline", "recent data" and "dirtier plants" in the remainder of the paper. We highlight our recent data model as the preferred specification because, reflecting changes in regulations and technology, these data are more predictive of how power plants will behave in the future. The dirtier plants specification address the concern that emissions reductions will not be randomly distributed across plants. In particular, if states implement emissions trading markets or impose a carbon tax, we would expect plants that emit more CO_2 per unit of output to have a stronger incentive to reduce CO_2 emissions.[4]

5.1 CO_2 emissions

We first estimate a model on CO_2 emissions. Although we focus on the impact of the CPP on emissions of SO_2 and NO_x, we can validate our approach by comparing our projected CO_2 emissions reductions with those reported by EPA. We can do this in two ways: 1) by comparing our estimated marginal effect of an additional MWh on CO_2 emissions with the established emissions factors, such as those reported by the EIA (EIA 2016), and 2) by comparing our overall estimated reductions in CO_2 emissions with the EPA's estimates. If our model produces marginal effects similar to these reported by the EIA and overall reductions similar to those reported by the EPA, then this would suggest that our approach is valid.

The results, in Table 3, indicate that for coal-fired facilities, the elasticity of CO_2 emissions with respect to output is about one (0.995) in our preferred specification using more recent data; when a coal plant increases output by one percent, CO_2 emissions rise by 0.995%. Similarly, the heat rate elasticity is a bit less than one (0.934). The results for gas plants indicate that the elasticity of CO_2 emissions with respect to output is smaller; when a natural gas facility increases output by one percent, CO_2 emissions increase by about 0.934 percent in the recent data model (recall that we do not include heat rate in the gas plant regressions, because increasing efficiency is only a mechanism for coal plants to reduce CO_2 emissions). Output elasticities are very similar across all three models (i.e. baseline, recent data and dirtier plants) for both coal and gas plants.

As a rough check on the validity of our approach, we compare our estimated marginal effects of output with those of the EIA. According to the EIA, one MWh of electricity produced by burning coal emits a little more than one ton of CO_2 (EIA 2016).[5] By comparison, one MWh of electricity produced by burning natural gas emits about 0.6 tons of CO_2. Thus, if our model produces marginal effects similar to these reported by EIA, then this would suggest that our approach is valid.

To calculate the marginal effect of a MWh of electricity produced in a coal-fired plant at the average value of CO_2 emissions/output for coal plants, we multiply our estimated elasticity of output (0.995) by the average value of CO_2 emissions/output (1.09 tons of CO_2/MWh) for coal-fired plants in 2014 (the most

[4] Because output reduction is the primary means of reducing CO_2 emissions, this will be least costly for the most CO_2-intensive plants.

[5] The exact amount depends on the type of coal burned (i.e. bituminous coal, subbituminous coal, lignite). The EIA estimates range from 1.035-1.085 tons of CO_2/MWh from coal and 0.61 tons of CO_2/MWh from natural gas

recent year for which eGRID data are available). This yields a marginal effect of 1.085 tons of CO_2 for an additional MWh of electricity produced by burning coal. Using the same approach for gas plants, we again calculate the marginal effect by multiplying our estimated elasticity of output (0.934) by the average value of CO_2/output (0.468 tons of CO_2/MWh) in 2014, which yields a marginal effect of 0.437 tons of CO_2 for an additional MWh of electricity produced with natural gas. Our marginal effect is consistent with the EIA's carbon emission factor for coal, a bit less so for natural gas. Regardless, these results provide evidence for the validity of our approach, particularly for the coal-fired plants. Importantly, as will become apparent below, the CPP's effect on emissions of CO_2 and local pollutants is driven almost exclusively by reductions in coal generation.

As our principal validity check, we use our estimated marginal effects, along with EPA projections of changes in generation and heat rate, to assess how much emissions will change if states achieve the CPP-mandated CO_2 emissions reductions targets (i.e., by reducing output and heat rate as projected by EPA). To do so, we examine the impact of the three mechanisms and then add up the effects. We begin by assessing the impact of the first mechanism: increasing the efficiency of coal-fired plants by reducing heat rate.

To project the heat rate reduction, the EPA assumed the following heat-rate improvements for the three major interconnections (EPA 2015a):

- Western Interconnection: 2.1 %.
- Eastern Interconnection: 4.3 %.
- Electric Reliability Council of Texas (ERCOT): 2.3 %.

In our sample, the vast majority (81%) of coal plants are in the Eastern Interconnection, and account for about 77% of output each year. Therefore, we simply take an output-weighted average of the three heat rate reduction estimates, which yields a 3.8 percent average reduction in heat rate. However, the EPA projects that only about 51% of coal capacity in 2030 will actually reduce its heat rate. We incorporate this estimate in the following formula in order to calculate the CO_2 emissions reductions attributed to heat rate:

$$\Delta\left(CO_{2_{Heat\ Rate}}\right) = C * b_{HR} * \Delta(Heat\ Rate) * CO_{2_{base}} \quad (1)$$

where:

$\Delta(CO_{2_{Heat\ Rate}})$ is the CO_2 reduction attributed to heat rate improvements

C is the capacity of coal plants (i.e. 51%) that the EPA expects will reduce their heat rate in 2030

b_{HR} is the estimated heat rate elasticity from Table 3 (Recent data model)

$\Delta(Heat\ Rate)$ is the weighted average reduction in heat rate (3.8%) discussed above

$CO_{2_{base}}$ is the CO_2 baseline emissions in 2030 according to EPA's projection (2.227 billion tons of CO_2)

Equation (1) yields a reduction of 40 million tons of CO_2 emissions in 2030 relative to the baseline level of projected emissions in the more recent data specification. In other words, our results indicate that coal plants will reduce CO2 emissions by 40 million tons in 2030, relative to the projected baseline, by reducing their heat rate (increasing their efficiency of production).

Next, we examine the effects of changes in output in both coal and gas plants.

To assess the magnitude of output's effect on emissions, we need to use EPA estimates for reductions in output in coal and gas plants, along with our estimated marginal effects for output in coal and gas plants. The EPA projects that electricity output in coal plants will fall by 322 million MWh in 2030, relative to the base case (EPA 2015a)[6]. At the same time, it projects that electricity output in gas plants will fall by 69 million MWh[7]. Note, that despite shifting output from coal to gas plants, output in gas plants (existing and new) is projected to fall due to increased demand-side efficiencies.

Equation (2) summarizes the calculation of CO_2 emissions reductions due to output reduction in coal and gas plants:

$$\Delta\left(CO_{2_{output}}\right) = \Delta\left(Q_{gas}\right) * b_{Qgas} * CO_{2_{Gas2014}} + \Delta(Q_{coal}) * b_{Qcoal} * CO_{2_{Coal2014}} \quad (2)$$

where:

$\Delta(CO_{2_{Output}})$ is the CO_2 reduction attributed to electricity output reduction from coal and gas plants

$\Delta\left(Q_{gas}\right)$ and $\Delta(Q_{coal})$ capture the electricity output reduction in gas and coal plants respectively, in 2030 (69 million MWh for gas plants and 322 million MWh for coal plants) based on EPA's projections.

$b_{Q_{gas}}$ and $b_{Q_{coal}}$ are the estimated output elasticities of gas and coal plants from Table 3 (Recent data model)

$CO_{2_{Gas\,2014}}$ and $CO_{2_{Coal\,2014}}$ capture the average ton of CO_2 per MWh for gas and coal plants respectively in our sample for 2014 (0.468 for gas plants and 1.09 for coal plants).

Finally, equation (3) illustrates the formula for the calculation of the overall CO2 reductions:

$$\Delta(CO_{2_{overall}}) = \Delta\left(CO_{2_{Gas\ output}}\right) + \Delta\left(CO_{2_{Coal\ output}}\right) + \Delta(CO_{2_{Heat\ Rate}}) \quad (3)$$

Table 4 shows the results for the overall CO_2 reductions for the three model specifications. The point estimate of our preferred specification (recent data) indicates a 420 million ton reduction of CO_2, which is a 18.9% reduction relative to the 2030 baseline. By comparison, the EPA projects total reductions of 413 million tons of CO_2 emissions (18.5% reduction). Thus, our approach yields an estimated reduction in

[6] Using the projections based on the mass-based approach.

[7] Including generation from existing and new plants.

CO_2 emissions about 1.7% higher than EPA's. As expected our dirtier plants specification yields a higher point estimate of 431 million tons (19% reduction). An additional contribution of our model is that we are able to calculate confidence intervals for the point estimates of CO_2 reductions. Those confidence intervals, presented in column 4 of Table 4 are calculated using the estimated standard errors of the output and heat rate elasticities in Table 3. Both the Recent data and Dirtier plants confidence intervals of Table 4 include EPA's 413 million ton estimate. As a result, even though our point estimates for the CO_2 reductions are higher than EPA's there are not statistically significantly different.

The level of precision of our newer data specification, evaluated versus EPA's estimates, provides strong evidence that our approach can be used to estimate the emissions impacts of the CPP. Taken together, the results in Tables 3 and 4 provide strong support for the external validity of our data-driven approach.

5.2 Co-pollutant emissions reductions

Having established the validity of our approach, we now turn to the main focus of our paper: the effects on SO_2 and NO_x emissions. Table 5 presents the output and heat rate elasticities for SO_2 and NO_x for coal and gas plants. As discussed earlier, we do not include heat rate in our gas plant models, because it is not a mechanism for reducing emissions in these plants. In addition, SO_2-pollution control devices were not used in any of the natural gas plants in our sample.

Column 1 of Table 5 indicates that the elasticity of SO_2 emissions with respect to output is about 0.506 for the recent data specification in coal plants. This implies that a 1% reduction in output from a coal plant will reduce SO_2 emissions by 0.51%. We also find that having SO_2-pollution control technology in all boilers of a given plant reduces SO_2 emissions by about 68 percent[8]. When we restrict our sample to the dirtier plants, a 1% output reduction decreases SO_2 emissions by 0.73%. This is primarily due to the fact that the dirtier plant specification includes older plants that prior to 2007 had higher SO_2 intensities.

In the second column of Table 5 we look at SO_2 emissions in gas plants. The elasticity for output there is 0.98 for the recent data specification. The output elasticities for SO_2 in gas plants are very similar across all three model specifications. This is likely because gas plants emit a trivial amount of SO_2 (as indicated in Table 2). The differences in output elasticities of SO_2 across coal plants are larger.

Column 3 presents the output and heat rate elasticities for NO_x in coal plants. In the recent data specification the elasticity is 0.83 compared to 1.17 for the dirtier plants model. In addition improving heat rate decreases the amount of NO_x emissions in coal plants (although that effect is not significant in the dirtier plants model). The effect of NO_x pollution control devices is not statistically significant in either type of plant.

The estimation of the elasticities in Table 5 is the main contribution of our work. These are output and heat rate elasticities that are empirically derived and can be used to predict the impacts of carbon abatement policies on the emissions of co-pollutants. Unlike the case of CO_2, there are no well-established elasticities for these co-pollutants in the literature. Therefore, we compare our projected overall co-

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[8] Given a coefficient, B, the effect of a change from 0-1 in a variable when the left-hand side variable is logged is computed as exp(B)-1.

pollutant reductions with those of the EPA, following a similar process as the one described in section 5.1. Equation (4) illustrates the emissions reductions formula for the case of heat rate:

$\Delta(Pollutant_{Heat\ Rate}) = C * b_{HR} * \Delta(Heat\ Rate) * Pollutant_{base}$ (4)

Where:

$\Delta(Pollutant_{Heat\ Rate})$ is the change in NO_x or SO_2 emissions attributed to heat rate improvements

C is the capacity of coal plants (i.e. 51%) that the EPA expects will reduce their heat rate in 2030

b_{HR} is the estimated heat rate elasticity from Table 5 (Recent data model)

$\Delta(Heat\ Rate)$ is the weighted average reduction in heat rate (i.e. 3.8%) discussed in section 5.1

$Pollutant_{base}$ is the SO_2 or NO_x baseline emissions in 2030 based on EPA's projection (1.314 million tons of SO_2 and 1.293 million tons for NO_x)

Next, we estimate the effect of output reductions in co-pollutant emissions, again using a similar approach as that described in section 5.1, namely:

$\Delta(Pollutant_{output}) = \Delta(Q_{gas}) * b_{Qgas} * Pollutant_{Gas2014} + \Delta(Q_{coal}) * b_{Qcoal} * Pollutant_{Coal2014}$
(5)

where:

$\Delta(Pollutant_{Output})$ is the co-pollutant reduction attributed to electricity output reduction from coal and gas plants

$\Delta(Q_{gas})$ and $\Delta(Q_{coal})$ capture the electricity output reduction in gas and coal plants respectively in 2030 (69 million MWh for gas plants and 322 million MWh for coal plants) based on EPA's projections

$b_{Q_{gas}}$ and $b_{Q_{coal}}$ are the estimated output elasticities of gas and coal plants from Table 5 (Recent data model)

$Pollutant_{Gas\ 2014}$ and $Pollutant_{Coal\ 2014}$ capture the average ton of co-pollutant emissions in tons per MWh for gas and coal plants respectively in our sample for 2014 (0.004 and 0.091 for SO_2 and NO_X respectively in gas plants; 1.616 and 0.94 for SO_2 and NO_x respectively in coal plants).

The combined effects of the change in heat rate and output (calculated using equations 4 and 5) are illustrated in Table 6. We find that the CPP should result in a 263 thousand ton (20%) reduction in SO_2 emissions in 2030 relative to base case emissions (1.314 million tons) based on the recent data model. By comparison, the EPA estimates that SO_2 emissions will be reduced by 280,000 tons (21%), relative to the 2030 baseline. For NO_x, our recent data specification estimates indicate a 285 thousand ton (22%) reduction relative to the 2030 base case emissions (1.293 million tons). This estimate is very close to EPA's prediction of 278 thousand tons of NO_x reductions. As expected our dirtier plants specification indicates higher co-pollutant reductions, consistent with the higher output elasticities estimated in Table 5.

Overall, our co-pollutant reduction estimates are not statistically significantly different from EPA's as indicated by the confidence intervals presented in column 4 of Table 6. This validates our strategy for estimating co-pollutant elasticities and allows us to explore different scenarios of co-pollutant reductions. We use the results presented in this section to determine the monetized value of health benefits from different policy scenarios.

6. Health effects

Having estimated the co-pollutant elasticities for SO_2 and NO_x, the next step is to examine how the CPP will affect human health. To do this, we need to calculate the amount by which electricity output must be reduced in order to generate the projected reduction in CO_2 emissions. Because we are concerned that the marginal effect of emissions on health is not constant, we will examine only the impact of a 1% reduction in CO_2 emissions (and therefore, the amount by which electricity output must be reduced to achieve this 1% reduction) rather than the health impact of reducing CO_2 by the full amount projected by the CPP (413 million tons). To estimate the reduction in output that will result from a 1% reduction in CO_2 (i.e. 1% of the total amount 413 million tons) we apply the coefficient from Table 3. Because that coefficient (0.995) pertains to the reduction of CO_2 from a 1% reduction in output, we calculate its reciprocal (i.e. 1/.995). We then use our output elasticities on SO_2 and NO_x to estimate the reductions in SO_2 and NO_x emissions from reductions in output attributed to a 1% reduction in CO_2. We cannot simply use our projected total reductions in SO_2 and NO_x emissions from above because we need to distribute these reductions in output and emissions at the plant level. That is, we do not assume that utilities will apply these reductions in output uniformly across plants. Rather, we assume that utilities will strategically shutdown facilities and/or reduce output at facilities. We consider four alternative schemes by which utilities might choose to implement these reductions.

1. Reduce emissions at dirtiest plants ("Dirty 1"): In this approach, we assume that utilities shut down and/or reduce output at the coal plants[9] with the highest CO_2 emissions/output ratio. They shutdown coal plants until they meet the CPP-mandated, mass-based state CO_2 emissions reduction target.
2. Reduce emissions at oldest plants ("Old"): In this approach, we assume that utilities shut down and/or reduce output at the oldest coal plants. Again, they shutdown coal plants until they meet the CPP-mandated, mass-based state CO_2 emissions reduction target.
3. Reduce emissions at plants with the lowest capacity utilization rate ("Capacity Utilization"): In this approach, we assume that utilities shut down and/or reduce output at the coal plants with the lowest capacity utilization rate.
4. Reduce emissions at plants in counties with the largest marginal damages ("Marginal Damages"): In this approach, we assume that utilities shut down and/or reduce output at the coal plants

[9] In all four schemes, we assume that utilities will achieve all emissions reductions by reducing output at coal facilities. In a small number of states, shutting down all coal plants does not achieve compliance with the CPP. In those cases, we assume that utilities satisfy the remaining reductions by reducing output at natural gas plants, using the same scheme.

located in counties with the largest marginal damages. Marginal damage data come from the EASUIR model (Heo 2015).

In all four of the above schemes, we use the coefficients from our preferred specification (using data only from 2007-14). As a robustness check, we re-run the first scheme, in which we assume that utilities reduce output at the most CO_2-intensive facilities, but we use the coefficients from our analysis of the dirtier (more CO_2-intensive) plants. We label this scheme, "Dirty 2".

The estimated reductions in co-pollutants from the various plants are aggregated at the county level and are then used as input in the "Estimating Air pollution Social Impact Using Regression" (EASIUR) model. The latter is an integrated assessment model that predicts the marginal damage from an increase in pollution at any point in the continental U.S. The marginal damage estimate is based upon the impact of ambient $PM_{2.5}$ on mortality in both nearby and downwind regions. In addition to varying across geographic space, predicted marginal damages vary with seasonal patterns in pollution transport, stack emission height, and pollutant type ($PM_{2.5}$, SO_2, NO_x, and NH_3). The EASIUR model was developed by Heo (Heo 2015). EASIUR is based upon another chemical transport and integrative assessment model, the Comprehensive Air Quality Model with Extensions (CAMx). EASIUR's damage predictions correlate well with the results from other integrated assessment models, including both CAMx and AP2.

The results from each of the four alternative schemes, as well as the robustness check, are presented in Figure 3. The horizontal dotted lines, represent the inferred health benefits due to SO_2 and NO_x reductions that arise as a result of a 1% reduction in CO_2, based on EPA's projections. For each co-pollutant, there are two sets of horizontal dotted lines capturing the two different concentration response ratios the agency used in the CPP RIA. Concentration response ratios indicate the relative risk of mortality per increase in ambient pollution. The light blue lines use the concentration ratio of Krewski et al. (2009), while the dark blue lines use that of Lepeule et al. (2012). For each co-pollutant, health benefits depicted in Figure 3 there are two sets of five vertical lines (one set for NO_X and one for SO_2). Each vertical line captures the health estimates from one of the four alternative schemes discussed above ("Dirty 1", "Old", "Capacity Utilization", "Marginal Damages") as well as the robustness check ("Dirty 2"). For SO_2, our health benefit estimates from a 1% reduction in CO_2, are not statistically significantly different from EPA's inferred $244 million (in 2011 dollars) using the Lepeule et al. (2012) concentration ratio. This suggests that, a 1% reduction in CO_2 emissions based on EPA's 2030 projections, will result in co-pollutant reductions that will yield health benefits of $244 million. For NO_x our estimated health benefits are higher than EPA's inferred estimates of $20 million (again using the Lepeule et al. (2012) ratio). Three of our five NO_x health estimates are at $65 million indicating that the EPA could potentially be underestimating the health benefits from NO_x reductions. Our 95% confidence intervals capture uncertainty from the elasticity estimates, value of statistical life, concentration response ratios, and the air quality modeling computations.

7. Conclusions

In August 2015, President Obama announced the final version of the Clean Power Plan, which established state limits on CO_2 emissions by power plants. The CPP sets state-specific targets for CO_2 emissions reductions, with the EPA providing states the flexibility to determine the best way to meet these targets. The EPA lists three mechanisms that states can use to achieve the CO_2 reductions: (1) reduce demand for electricity; (2) shift the fuel mix from more carbon-intensive energy sources (coal) to less carbon-intensive source (natural gas) and zero-carbon fuels (renewables); and (3) reduce the plant's heat rate.

In total the EPA projects that US power plants will reduce CO_2 emissions by 19% in 2030 relative to baseline levels. While the primary focus of the CPP is reducing CO_2 emissions to slow climate change, an important element of the plan is that by reducing CO_2 emissions, plants will also reduce emissions of SO_2 and NO_x. These local pollutants have been shown to have a variety of negative health effects including increased respiratory diseases, increased asthma attacks, and greater mortality, among others. The EPA estimates that the health benefits from reducing emissions of these local pollutants are large: roughly as large, or larger than the climate change benefits from reducing CO_2 emissions, the primary target of the plan.

The standard approach for assessing the impact of regulations like the CPP on the behavior of power plants is to use LP models. In this paper, we consider a different approach to assess the impact of the CPP: we use historical data from power plants to estimate how much the CPP will reduce emissions of local pollutants, SO_2 and NO_x. To do so, we use ten years (spanning 1998-2014) of eGRID data on US power plants to assess how much the EPA's building blocks affect emissions of SO_2 and NO_x. Because our approach is a novel one, we first test its validity by estimating the projected reductions in CO_2 emissions. Our model projects CO_2 emissions reductions within 1.7% of EPA projections. Using our estimates, we then project how much SO_2 and NO_x emissions would fall if plants reduce output and increase efficiency as projected by the EPA. Our preferred specification suggests that a 1% reduction in electricity output from coal plants would results in a 0.8% reduction in NO_x and a 0.5% reduction in SO_2. A similar output reduction in gas plants would result in a 0.7% reduction in NO_x. Using those elasticities as well as the predicted output reduction from the CPP provided by the EPA, we calculate the total reductions in SO_2 and NO_x. In both cases, our results are not statistically different than EPA predictions, a fact that validates our empirical approach. Furthermore, we estimate the monetary value of these reductions and compare our estimates to the EPA's. While our estimates acknowledge that there is substantial uncertainty, our point estimates for the monetary benefit from SO_2 reductions are not statistically different than the EPA's. However, our estimates suggest that the EPA may be underestimating the value of NO_X reductions as their point estimate lies outside out our 95% confidence interval.

More generally, our results suggest that, in the absence of strong evidence that the effects of mechanisms under power plant control have changed markedly, there is value in using an empirical approach to project the regulatory impacts of EPA interventions, rather than relying exclusively on engineering-based, integrated planning models.

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Table 1

Total Annual Generation: Plants with Observed Emissions vs Plants with Imputed Emissions

	Total Generation (GWh)	
Year	**Plants with Observed Emissions**	**Plants with Imputed Emissions**
1998	1,623,711	1,954,085
1999	1,524,171	2,133,085
2000	1,538,793	2,230,741
2004	1,972,511	1,949,731
2005	2,183,049	1,860,369
2007	2,326,383	1,822,433
2009	2,293,367	1,644,650
2010	2,448,960	1,663,162
2012	2,404,131	1,641,387
2014	2,636,260	1,443,431

Table 2
Summary Statistics for Coal and Gas Plants

		Coal Plants		Gas Plants	
Variable	**units**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Net generation	MWh	5,999,173	4,933,600	1,147,536	1,751,053
CO_2 emissions	tons	6,605,849	5,275,422	535,917	785,576
SO_2 emissions	tons	20,151.99	26,383.87	3.77	18.84
NO_x emissions	tons	9,490.04	10,626.69	174.25	609.74
Heat rate	Btu/kWh	11,015.80	1,276.58	NA	NA
SO_2 control devices	% plant operating hours	0.54	0.47	0	0
NO_x control devices	% plant operating hours	0.91	0.28	0.92	0.38
N	plant-years	1,594		3,656	

Table 3

The effect of output and heat rate on CO_2 emissions

	Coal plants		Natural Gas Plants	
	Coefficient (elasticity)	Marginal effect per MWh of output (in tons)	Coefficient (elasticity)	Marginal effect per MWh of output (in tons)
Baseline model				
Ln_Output	1.006***	1.097	0.899***	0.421
	(0.008)		(0.019)	
Ln_Heat_Rate	0.983***			
	(0.019)			
Number of plant-years				
Recent data model				
Ln_Output	0.995***	1.085	0.934***	0.437
	(0.004)		(0.018)	
Ln_Heat_Rate	0.934***			
	(0.058)			
Number of plant-years				
Dirtier plants model				
Ln_Output	1.028***	1.121	0.889***	0.412
	(0.018)		(0.057)	
Ln_Heat_Rate	0.964***			
	(0.076)			

All models include plant and state-year fixed effects and plant specific time trends. In all models we weight each observation by plant output (MWh of electricity produced). *p<.05 **p<.01.

Table 4

Total reductions of CO_2 (in million tons)

	1	2	3	4	
CO_2 reduction due to:	Coal plants	Gas plants	Total	95% C.I.	
Baseline model					
Output	353	29			
Heat rate	42.4				
Total	395.4	29	424.4	416	433
Recent data model					
Output	349	30			
Heat rate	40				
Total	389	30	420	411	429
Dirtier plants model					
Output	361	28			
Heat rate	42				
Total	403	28	431	408	454

Table 5

The effect of output and heat rate on SO_2 and NO_x emissions

	1	2	3	4
	SO_2		NO_x	
Baseline model	Coal plants	Natural Gas Plants	Coal plants	Natural Gas Plants
Ln_Output	0.766***	0.934***	0.943***	0.617***
	(0.141)	(0.032)	(0.081)	(0.040)
Ln_Heat_Rate	0.443		1.072***	
	(0.269)		(0.299)	
Control devices	-1.398***		0.092	-0.066
	(0.200)		(0.132)	(0.047)
Number of plant-years				
Recent data model				
Ln_Output	0.506**	0.980***	0.828***	0.689***
	(0.207)	(0.035)	(0.105)	(0.044)
Ln_Heat_Rate	-0.833		1.194***	
	(0.654)		(0.290)	
Control devices	-1.129***		0.047	-0.031
	(0.162)		(0.184)	(0.035)
Number of plant-years				
Dirtier plants model				
Ln_Output	0.728***	0.957***	1.168***	0.866***
	(0.198)	(0.123)	(0.127)	(0.062)
Ln_Heat_Rate	0.731		0.552	
	(0.526)		(0.623)	
Control devices	-2.378***		-0.058	0.006
	(0.357)		(0.109)	(0.005)

All models include plant and state-year fixed effects and plant specific time trends. In all models we weight each observation by plant output (MWh of electricity produced). †$p<.10$ *$p<.05$ **$p<.01$.

Table 6

Total reductions of NO_x and SO_2 (in thousand tons)

	1	2	3	4		
NO_x reduction due to:	Coal plants	Gas plants	Total	95% C.I.		EPA projection
Baseline model						
Output	285	4				
Heat rate	27	N/A				
Total	312	4	316	250	382	278
Recent data model						
Output	251	4				
Heat rate	30	N/A				
Total	281	4	285	205	365	278
Dirtier plants model						
Output	393	17				
Heat rate	N/S	N/A				
Total	393	17	410	319	502	278
SO_2 reduction due to:	Coal plants	Gas plants	Total	95% C.I.		EPA projection
Baseline model						
Output	399	0				
Heat rate	N/S	N/A				
Total	399	0	399	250	548	280
Recent data model						
Output	263	0				
Heat rate	N/S	N/A				
Total	263	0	263	44	483	280
Dirtier plants model						
Output	430	0				
Heat rate	N/S	N/A				
Total	430	0	430	187	674	280

Figure 1

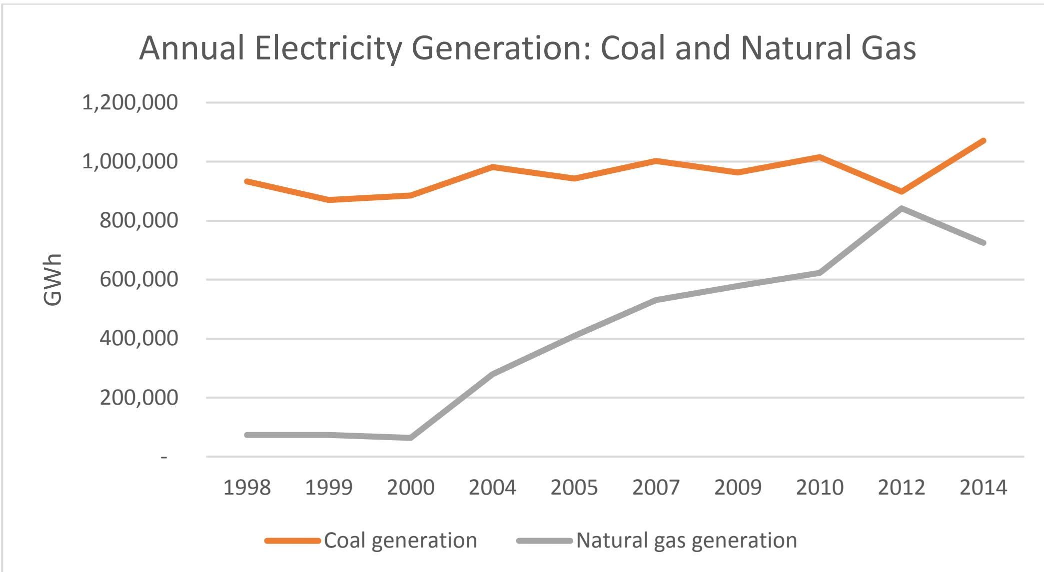


Figure 2

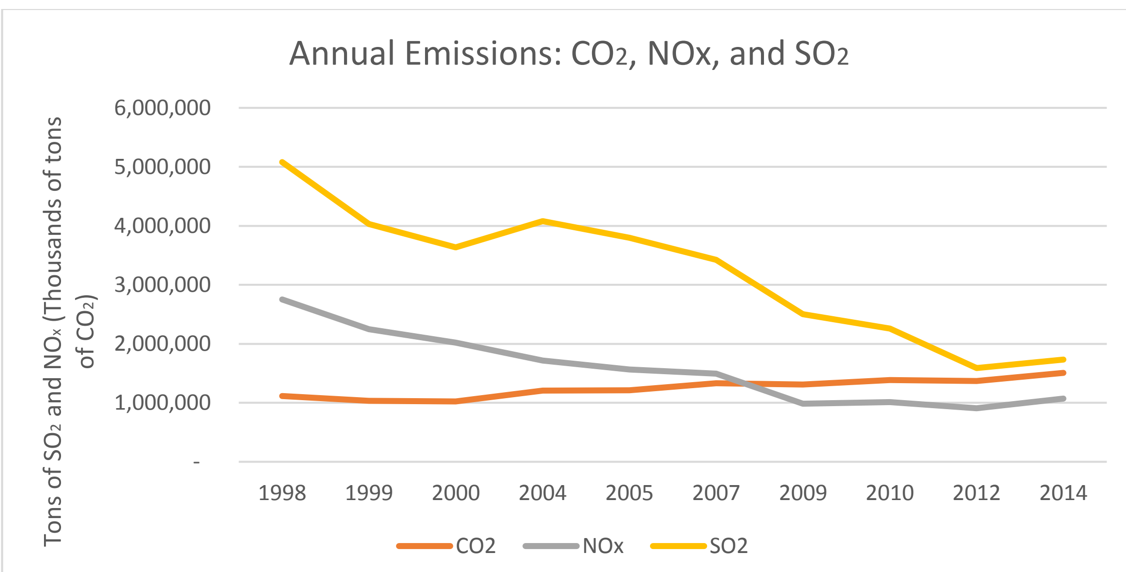
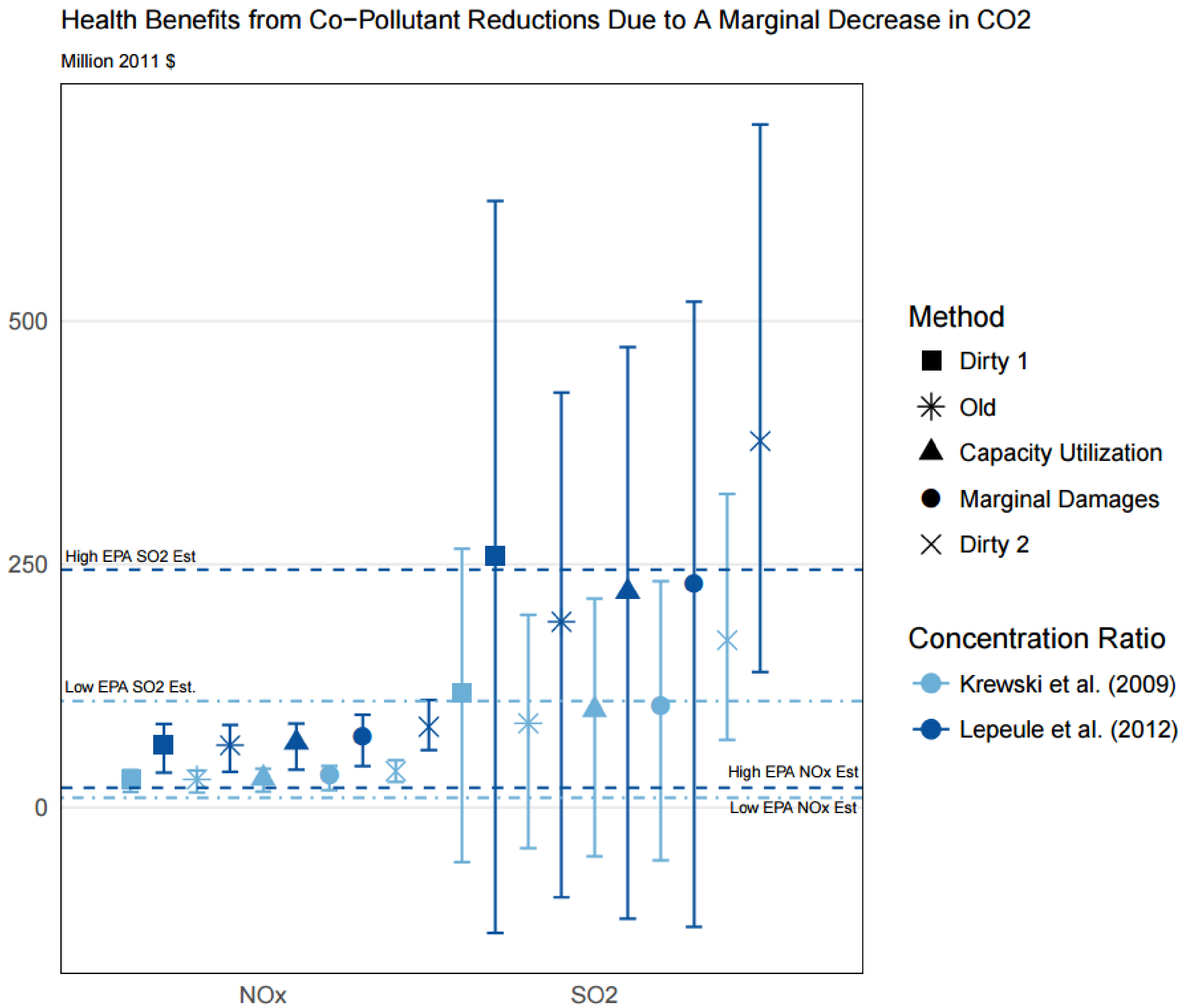


Figure 3


Health Benefits from Co−Pollutant Reductions Due to A Marginal Decrease in CO2
Million 2011 $
500
250
0
High EPA SO2 Est
Low EPA SO2 Est.
High EPA NOx Est
Low EPA NOx Est
NOx
SO2
Method
Dirty 1
Old
Capacity Utilization
Marginal Damages
Dirty 2
Concentration Ratio
Krewski et al. (2009)
Lepeule et al. (2012)

Appendix 1

List of SO_2 and NO_x control Devices in eGRID Source: EPA (EPA 2008)

List of SO_2 control devices	**List of NO_x control devices**
Jet bubbling reactor	Advanced overfire air
Circulating dry scrubber	Biased firing
Dual alkali	Fluidized bed combustor
Dry lime flue gas desulfurization unit	Combustion modification/fuel reburning
Fluidized bed	Dry low NO_x premixed technology
Mechanically aided type	Flue gas recirculation
Magnesium oxide	Fuel reburning
Other	Water injection
Packed type	Low excess air
Sodium based	Low NO_x burner
Spray dryer type	Low NO_x burner with overfire air
Spray type	Low NO_x burner technology with close-coupled overfire air
Tray type	Low NO_x burner technology with separated OFA
Venturi type	Low NO_x burner technology with close-coupled and separated overfire air
Wet lime flue gas desulfurization unit	Low NO_x burner technology for cell burners
Wet limestone	Ammonia injection
	Overfire air
	Slagging
	Selective catalytic reduction
	Selective noncatalytic reduction
	Steam injection